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Poverty and Income Seasonality in Bangladesh

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Abstract

Seasonal poverty in Bangladesh, locally known as *monga,* refers to seasonal deprivation of food during the pre-harvest season of *Aman* rice. An analysis of household income and expenditure survey data shows that average household income and consumption are much lower during monga season than in other seasons, and that seasonal income greatly influences seasonal consumption. However, lack of income and consumption smoothing is more acute in greater Rangpur, the North West region, than in other regions, causing widespread seasonal deprivation. The analysis shows that agricultural income diversification accompanied by better access to micro-credit, irrigation, education, electrification, social safety net programs, and dynamic labor markets has helped reduce seasonality in income and poverty in regions other than Rangpur in the recent past. Hence, government policies should promote income diversification through infrastructure investments and provide income transfers to the targeted poor to contain income seasonality and poverty in this impoverished part of Bangladesh.

This paper—a product of the Sustainable Rural and Urban Development Team, Development Research Group—is part of a larger effort in the department to understand the role of microfinance and other policy interventions to reduce seasonality in income and poverty. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The author may be contacted at skhandker@worldbank.org.

Poverty and Income Seasonality in Bangladesh

By

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Poverty and Income Seasonality in Bangladesh

1. Introduction

Smoothing consumption is a major problem for rural households in many agrarian societies. There is a large body of literature on seasonality in income, consumption, and poverty. Household incomes vary seasonally, often quite sharply.[2] Like income, household consumption levels also vary seasonally (Chambers, Longhurst and Pacey 1981; Chaudhuri and Paxson (2001); Sahn 1989; Paxson 1993; Dercon and Krishnan 2000). It is frequently asserted that the observed seasonality in consumption is largely driven by the seasonal variation in income, and that lack of proper credit markets impedes consumption smoothing. Consumption seasonality may also be pronounced due to non-credit factors such as seasonal variation in prices, preferences, labor efforts and precautionary savings motives (e.g., Chaudhuri and Paxson 2001; Paxon 1993).[3]

There is an extensive literature that shows that households adopt a wide range of strategies to undo or lessen the adverse affects of seasonality in income – counting on their own food and other asset stocks, remittance, receipts from the safety-net programs, selling assets, advance sale of labor and/or crops, and borrowing from formal and informal sources, etc. (e.g., Alderman and Paxson 1992; Besley 1995; Deaton 1992; Jalan and Ravallion 1999). Land fragmentation, storage of grain, accumulation of buffer stock, and mutual insurance (provided by family or friends) are some of the traditional risk management devices. Often

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[2] For example, in the ICRISAT sample of Indian villages used in Chaudhuri and Paxson's (2001) study, agricultural households, on an average, received 75 percent of their annual income in a three-month period.
[3] For instance, Paxson's (1993) findings suggest that in rural Thailand the observed seasonality in consumption patterns results from variation in prices or preferences, which are common to all households, rather than from the inability of households to use savings or borrowings to smooth consumption.

these devices can be very costly for households. Townsend (1995) shows that access to financial institutions (banks, credit unions, local money lenders) is important, and can often dramatically improve insurance over the traditional insurance mechanisms. Pitt and Khandker (2002) find that micro-credit can help smooth seasonal consumption by financing new productive activities whose "income flows and time demands do not seasonally co-vary with income generated by existing activities of households."

Indeed, evidence suggests that credit constraints prevent poor households from smoothing consumption across seasons and years (Behrman, Foster and Rosenzweig, 1997; Harrower and Hoddinott, 2004; Rosenzweig 1988; Rosenzweig and Wolpin 1993; Chaudhuri and Paxson, 2001). Rosenzweig and Binswanger (1993) find that in their efforts to diversify risk (e.g., selling livestock) less-wealthy farmers suffer from serious losses of efficiency. Informal credit may be still another way to smooth consumption, but this mechanism appears to be a costlier one, given its terms, from a household efficiency standpoint, and also susceptible to failing completely in the event of an aggregate shock. A well functioning credit market may help avoid the abrupt decline in consumption.[4] Public income transfer is another way to reduce the severity of consumption shortfalls (Matin and Hume 2003).

Seasonality in income and consumption does not necessarily follow starvation or hunger. Households have alternative ways to smooth consumption and thus avoid starvation. However, when income smoothing does not happen, a failure to smooth consumption may result in food shortage and deprivation (Dostie, Haggblade, and Randriamamony 2002; Dercon and Krishnan 2000; Muller 1997; Rahman 1995).[5]

[4] However, a complicating factor is that households may still be able to smooth consumption in the absence of properly functioning credit markets (controlling for price and preference) (Chaudhuri and Paxson 2001; Deaton 1991; Kazianga and Udry 2006). Households may do so using mechanisms such as buffer stock or interfamily transfers.

[5] In Madagascar, for example, seasonal fluctuation in rice production forces 1 million people to succumb to poverty during the lean season (Dostie, Haggblade, and Randriamamony 2002).

Bangladesh is a typical country with pronounced seasonality in income and consumption causing sometimes starvation en masses. Its agricultural sector is characterized by three crop seasons, based on three kinds of rice – *Aus*, *Aman* and *Boro*. While these three crops cover the whole year, there is a period of virtual economic inactivity during the lean period (Rahman 1995). The non-farm sector is not large enough to employ the unemployed who are mostly agricultural laborers or small farmers.[6]

The greater Rangpur district, the North West part of Bangladesh, experiences most seasonal deprivation, or what is commonly known as monga, during the pre-harvest season of aman rice.[7] Generally speaking, *monga* means scarcity of food and other essentials in Bangladesh and goes from September to November. In the greater Rangpur, *monga* refers to seasonal deprivation of food during lean months of the year when households do not have adequate employment, income, savings, and, hence, are subject to deprivation of food.[8]

Part of the inability of households to smooth consumption is due to a severe shortage of cash or a lack of access to credit markets. In the absence of well-functioning credit markets, households are frequently drawn to an informal credit market arrangement locally known as *dadan* to smooth consumption. *Dadan* refers to arrangements whereby laborers sell labor or farmers sell crops in advance to smooth consumption during *monga*. The terms often are quite severe to the sellers.

Households also adopt means such as distress sale of assets or seasonal migration to cope with *monga*. People also skip meals when they are unable to manage *monga* through any of the above means. Households who cannot cope with the severity of shortfalls in income,

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[6] Besides, non-farm activities are very much linked to farm activities.

[7] The greater Rangpur consists of five districts—Rangpur, Gaibandha, Kurigram, Lalmonirhat, and Nilphamari. Monga refers to "mora kartik" in greater Rangpur referring to the months of lean season of September and November.

[8] Note that *monga* does not necessarily mean shortage of food in this part of the country. It is rather a lack of purchasing power, income and employment for a large section of people (Sen 1981).

employment and food are bound to starve for an extended period. This leads to serious malnutrition and death in extreme circumstances.

But seasonality in agriculture is a basic fact of agrarian life. Households must be able to adopt effective ways to smooth consumption via income smoothing and other means so as to avoid seasonal hunger. Government policies must come to aid households in need of smoothing consumption. However, when none of these means is effective, a failure to smooth consumption results in *monga* or starvation. The intensity of *monga* varies by households and local socio-economic conditions and the extent of flood or drought preceding the *monga* period. *Monga* is a reflection of not only seasonality of agriculture but also a failure of public policies and programs that are expected to mitigate seasonality in income and consumption.

This paper discusses the extent of seasonality in income, consumption, and food deprivation using the nationally representative household income and expenditure surveys (HIES) of 2000 and 2005, carried out by the Bangladesh Bureau of Statistics (BBS). As the data are drawn over two periods, this paper will examine the changes in the severity of *monga* in greater Rangpur vis-à-vis other regions of Bangladesh over time. The paper makes an attempt to identify the causes (both seasonal and non-seasonal dimensions) of *monga* and determine possible short- and long-term remedies of seasonal poverty. An important aspect of the policy exercise is to identify the role of targeted programs such as micro-credit and the vulnerable group feeding (VGF) program in mitigating *monga*.[9]

[9] VGF program, administered by the government, provides food to a select number of households in a community that are affected by disasters or during a period when acquiring food is difficult for beneficiary households. Priority is given to households with low income, lacking agricultural land or other productive assets, day laborers or those headed by women. In a normal year, a distressed household receives 2 to 3 months of food rations, with no work or labor participation required.

The paper is organized as follows. Section two examines the patterns of seasonality in income, consumption and poverty in Bangladesh using the household income and expenditure surveys (HIES) of 2000 and 2005. Section three discusses the model of consumption smoothing and its estimation strategy. Section four presents the results on whether income seasonality affects consumption. Section five presents the results of the impacts of income seasonality on poverty. Section six assesses the impact of policies and programs on mitigating seasonality in consumption and poverty. And lastly, section seven summarizes the paper with policy implications.

2. Household welfare and seasonality in Bangladesh

Given that Bangladesh is an agrarian economy, the important policy question is: how much seasonality in agriculture matters to consumption and income? If *monga* is a seasonal poverty and only pronounced in greater Rangpur, does it mean that seasonality in agriculture is less pronounced in other regions of Bangladesh? The extent of seasonality in income and consumption can be shown through a disaggregate analysis of income and consumption data by season. In HIES surveys, households were interviewed at various times of the year across the country. Consumption and income data were collected, among other information, from all households. For example, income data was collected on crops, non-crop and non-farm sources over a year preceding the date of interviews. Thus, although seasonality in income of all types (especially non-farm) could not be traced for alternative seasons, the crop income can be sorted out by season because we know which crop is grown during which months of the year. On the other hand, for consumption, it is possible to categorize it by season based on the information collected for the week and the month preceding the date of interview. Thus, the HIES data can be arranged to show seasonality in income and consumption and its consequences in household welfare such as poverty.[10]

According to the distinct seasonal cycle of agricultural production, we group both consumption and income information into 4 seasons in terms of the harvest period of 3 main crops in Bangladesh—Aus, Aman, and Boro. The 4 seasons are the Boro (March-May), Aus (June-August), pre-harvest Aman, which is the *monga* period (September-November), and Aman (December-February).[11]

Figure 1 represents food consumption of rural households based on the HIES of 2000 and 2005. In both years, the overall food consumption per capita is much lower in Rangpur than the rest of the country, although the level of food consumption has increased in greater Rangpur in 2005 compared to the level of 2000. However, the seasonality in food consumption is much more pronounced in Rangpur than in other regions. Food consumption falls sharply during the pre-harvest period (i.e., *monga* period). This clearly indicates that seasonality in agriculture must result in severe shortfalls in food and, perhaps, starvation without recourse to other means to cope with the shortfall. [12]

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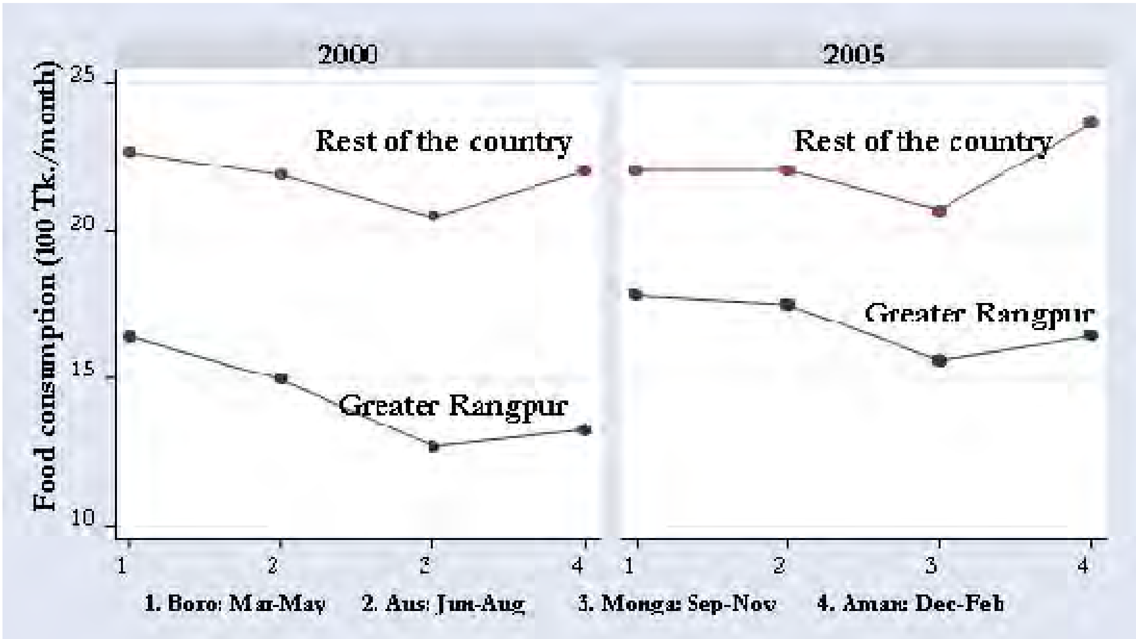
[10] The HIES survey of 2000 included a total sample of 7,440 households of which 5,040 households were drawn from rural areas. In 2005, the rural sample was 6,040 out of a total sample of 10,080 households This paper deals with the rural samples of both surveys.

[11] Note that Bangladesh has only 3 seasons based on crop cycle—Aus, Aman, and Boro. We create another season as pre-Aman or monga period o define whether household response behavior differs in pre-Aman compared to other seasons.

[12] Seasonal pattern in food consumption may reflect seasonal pattern in prices as well. In particular, if prices of food also fall (due to lower demand, foe example), it is not clear whether lower food consumption reflects seasonality in consumption of food quantity or food prices. For this, we examine patterns of food calorie intake (not shown here), which follows a similar seasonal pattern as food consumption.

Figure 1: Monthly food consumption by season



Sources: HIES surveys, 2002 and 2005.

Since consumption is falling at a similar rate across Rangpur and other regions, consumption, however, seems to remain lower even after monga in Rangpur as compared to the rest of the country. That is, the ability of rural households to recover from a sharp decline in consumption after the *monga* period is greater for the rest of the country than in Rangpur. In any case, the sharp decline in consumption during the lean season must be a major cause of widespread seasonal food deprivation or *monga* at least in Rangpur in 2005.

Food consumption is cyclical in response to crop seasonality in agriculture, and, hence, income. Because many rural households depend on income from crops, their income is likely to be seasonal.[13] Consider now the seasonality in income calculated based on the

[13] Food consumption is based on consumption during the weeks and months preceding the interview, and since households interviewed were distributed over a year, seasonality can be captured from the inter-household variation in food consumption, as opposed to intra-household variation. Income data, on the other hand, refers to the income of the entire year and therefore does not reflect seasonality. However, a seasonal variation can be detected in income by identifying households' income from crop production. Crop production

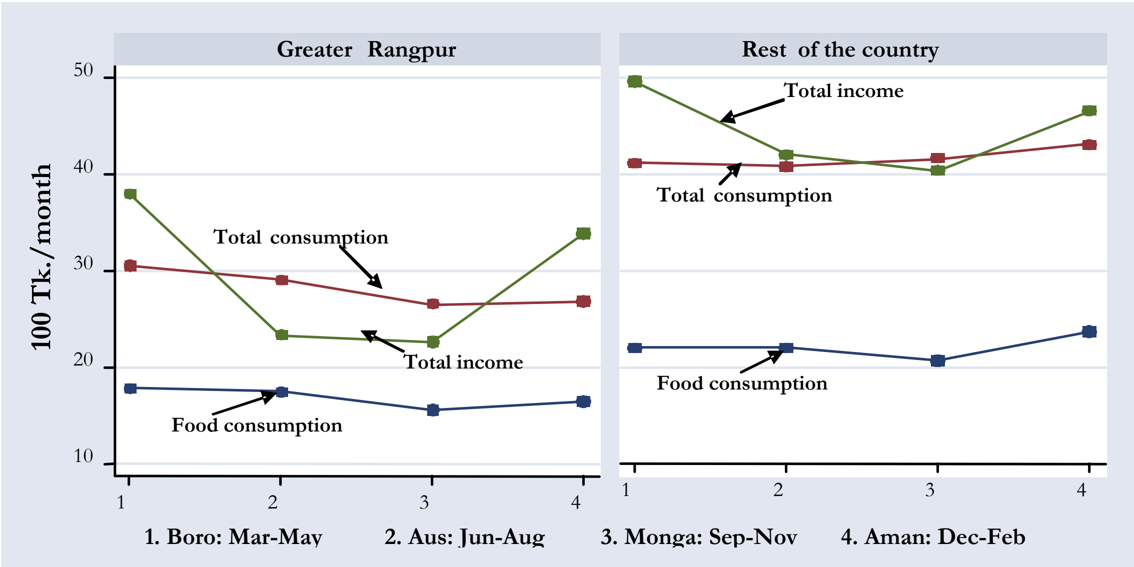
crops grown by households and the timing of their harvests. Crop income is added to income from other sources to obtain total per capita income. Figure 2 shows seasonality in both total income and total consumption per capita. It shows that income, especially crop income, is very much seasonal and follows a similar pattern of seasonality as consumption. The income of Rangpur is much lower as well as more seasonal than that of other regions. Like consumption, per capita income falls sharply during the *monga* period in Rangpur. There is seasonality in income of other regions but it is less pronounced compared to Rangpur.

There is a distinct pattern of income and consumption seasonality in Rangpur and other regions. As shown in figure 2, although food consumption, on an average, is far below the monthly income in all regions, total income falls short of total consumption during the *monga* period in both regions. More strikingly, however, in greater Rangpur the income falls short of consumption during other seasons as well, particularly during pre- *monga* and to some extent in the post *monga* period.

The fact that seasonality influences household's consumption does not mean that seasonal poverty will result as a consequence. Similarly, even if consumption smoothing varies by region, it does not tell us how much poverty is actually caused by seasonality (either idiosyncratic or aggregate). More specifically, as shown in Figure 2, we do not know how many households cannot smooth consumption and thus fall into seasonal hunger or poverty.

in Bangladesh is seasonal and diverse across households. Since, HIES collected households' crop income by specific crop, it is possible to calculate the share of households' seasonal crop income to total income.

Figure 2: Monthly income and consumption by season (2005)



Sources: HIES survey 2005.

This requires an examination of household poverty against seasonal income and consumption data to find out the extent of poverty in a particular season.

We propose that seasonality affects household's ability to maintain a minimum livelihood. A decrease in seasonal income lowers household's consumption. It lowers consumption enough to force many households down below poverty level. The question is how many rural households experience seasonal hunger during the lean season.

We consider three poverty indicators and their seasonal variations: moderate poverty, food poverty and extreme poverty. A household is considered moderate poor if its per capita expenditure (food and non-food) is less than the total poverty line established for the region as defined in Table 1.[14] Similarly, a household is considered food-poor if its per

[14] Table 1 shows regional food and total poverty lines for 2000 and 2005. It illustrates that the living expenditure in the Rangpur region is less than that in rest of the country, after adjusting for the consumer price index. It also shows that there has been very little increase in the poverty lines between 2000 and 2005.

capita food consumption is less than the food poverty line established for the region.[15] Extreme or hard-core poverty is on the other hand usually characterized by a situation when a household, with combined expenditure on food and nonfood, cannot match the food poverty line, let alone the total poverty line. So, extreme poverty indicates a dire economic situation, much worse than food poverty. [16]

Table 2 reports the distribution of moderate, food and extreme poverty for rural households, disaggregated by region and season, for 2000 and 2005. There are four basic trends observed from these poverty figures. First, the poverty situation is worse in the Rangpur region than in the rest of the country. Second, the poverty situation is worse during the *monga* period than during the non-*monga* periods. Thirdly, the poverty situation improves from 2000 to 2005. Finally, the gap in poverty status between the *monga* and non-*monga* periods is larger in the Rangpur region than in rest of the country, which is consistent with our earlier finding that consumption seasonality in the Rangpur region is higher than that in other regions. For example, the gap is about 12 percentage points for food poverty in the Rangpur region in 2005, whereas it was 7 percentage points in the rest of the country.

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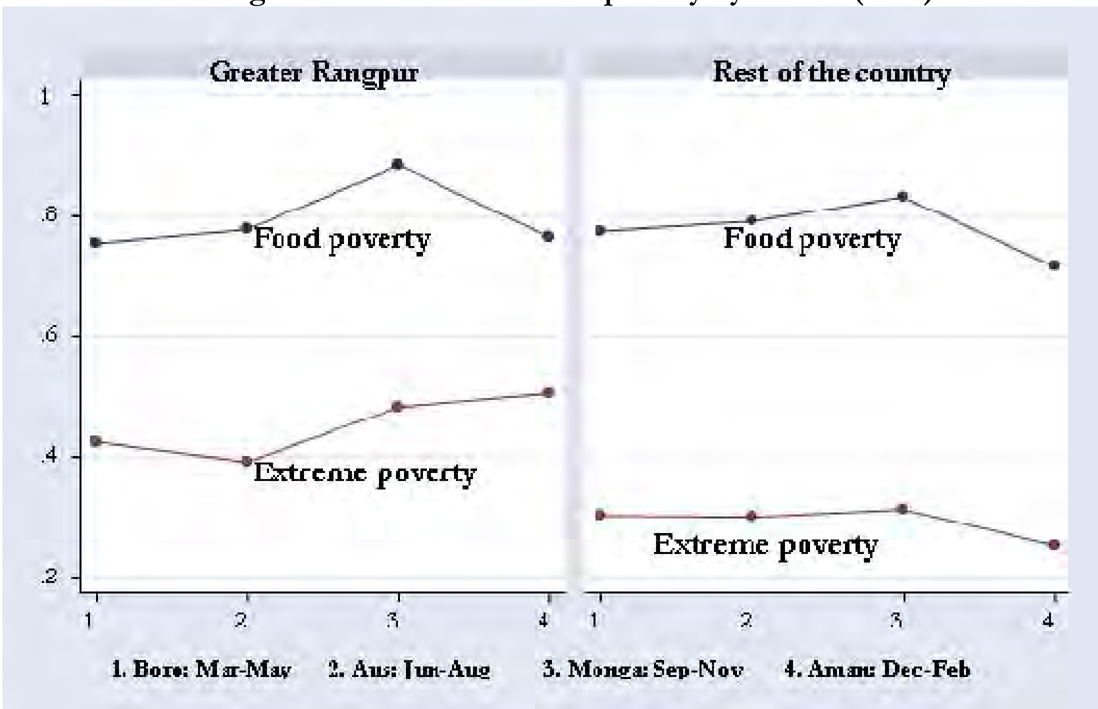
[15] Food poverty line is calculated by estimating the cost of a food basket needed to maintain the per capita daily caloric requirement (2112 calories) recommended by FAO (Food and Agricultural Organization). Since, household's food consumption calculated from HIES data refers to the consumption during the prior month's interview, the calculated food poverty is monthly and, hence, seasonal.

[16] The question may arise whether poverty figures represent any role of seasonal dimension. Note that consumption aggregates, the basis for poverty calculation, include both food and non-food. However,, more than 80 percent of total expenses comprise of food expenses. The information on food and some non-food expenses is drawn weekly and monthly data and hence, displays seasonality. But some non-food expenses are drawn from yearly data. However, to the extent that the non-food expenses do not vary much across seasons, the poverty (either moderate or extreme) figures would display seasonality primarily driven by seasonality in food consumption.

Figure 3: Food and extreme poverty by season (2005)



Sources: HIES survey 2005

Now take a closer look at the seasonal trends of these poverty indices in 2005. In figure 3 above, the year of 2005 is broken down into three seasons, as has been done for two earlier figures. The pattern in food poverty is similar in Rangpur and the other regions – it continuously increases and peaks during the *monga* season before declining in the post-*monga* season. The trend for extreme poverty is almost similar for the rest of the country. However, in the Rangpur region extreme poverty decreases during the pre-*monga* season and afterwards rises continuously, even during the post-*monga* season. This implies that although households in the Rangpur region manage to reduce their food deprivation during the post-*monga* period, their total consumption goes down, which is possible only if their non-food consumption falls significantly.

However, monga is perhaps more than seasonality of income and poverty in greater Rangpur. A World Bank study shows that the greater Rangpur was the most lagging region in Bangladesh in 2005 in terms of poverty reduction ((Narayan, Yoshida and Zaman 2007). This is indeed echoed in Table 3. In 2005, for example, greater Rangpur had a rural poverty rate in 2005 as high as 61 percent compared to only 45.1 percent poverty at the national level Extreme poverty was as high as 47.9 percent compared to the national rural average of 31.1 percent. Although Rangpur experienced a greater reduction of poverty over time (say between 2000 and 2005), the region is still lagging compared to the rest of the country in term of overall poverty figures.

More importantly, the Rangpur region is lagging in terms of other socio-economic indicators of household and community –level welfare. For example, household per capita income in Rangpur was about two-thirds of that in the rest of the country and this proportional share has remained constant over the years (Table 4). Households of greater Rangpur drew income more from farm than non-farm sources, thereby being more vulnerable to seasonality of agriculture. Greater Rangpur is also lagging in terms of access to credit and other infrastructures. More households draw wage income from agriculture in Rangpur (13.5 percent) than in the rest of the country (9.4 percent). However, agricultural wage workers fare worse in Rangpur than their counterparts in the rest of the country. For example, in 2005, the daily real wage rate for male agricultural workers in Rangpur was only 46 Taka compared to 64 Taka in the rest of country.[17]

[17] The higher wage rate in rest of the country reflects of a much more integrated wage market with outside the region which may reflect a higher rate of out-migration, implying an active shortage of labor with consequential higher wage rates.

3. Testing lack of income and consumption smoothing: Estimation strategy

Having shown the extent of seasonality in income, consumption and poverty, the next issues are: How much seasonality of income matters in seasonal variations of consumption and poverty? How much seasonal fluctuation in consumption and poverty is structural, making households incapable of managing seasonality efficiently?[18] Given the large body of literature which indicates that perfect consumption smoothing is possible even in the presence of a binding credit and other constraints, we need to estimate a consumption smoothing model to determine the extent of the role of income seasonality or lack of income smoothing in consumption and poverty.

Following Paxson (1993) and Deaton (1997), consider that the outcome variable C_{ijs} (the per capita consumption expenditure of household *i* in village *j* in season *s*) would depend on total per capita income (*Y*) and its seasonal shares (*y*) (this is essentially seasonal income), seasonal dummies, prices and preferences. Despite the fact that income data is subject to a measurement error (Deaton 1997), this income-consumption model is a standard model used to estimate the impact of income seasonality in consumption (e.g, Paxson 1993; Kazianga and Udry 2006)). Consider the following consumption equation in semi-logarithm form, conditional on total income (*Y*) and seasonal crop income shares (*y*):

$$\ln C_{ijs} = \alpha\tau_s + \beta_1 \ln Y_{ij} + \beta_2 y_{ijs} + \gamma X_{ij} + \mu_{ij} + \eta_j + \varepsilon_{ijs} \qquad (3.1)$$

where X_{ij} is a vector of household and village level characteristics (including prices) influencing consumption and income, and τ_s is seasonal dummies representing the

[18] The first question relates to finding the extent of idiosyncratic shock, while the second question refers to the aggregate shock on consumption and poverty. Policies to address them will differ by the severity of each type of shock.

seasons.[19] ε_{ijs} is a mean zero disturbance term that reflects unmeasured determinants of C_{ijs} that vary across households. Note also that household consumption is affected by unobserved household heterogeneity (μ_{ij}) and village heterogeneity (η_j).

If $\beta_2 = 0$, seasonality is not an issue and seasonal income does not track seasonal consumption with possible household's ability to smooth consumption through self-insurance and other mechanisms. That is, seasonal consumption depends entirely on overall income and not on seasonal income. Households are thus able to draw resources from alternative sources to compensate for losses in income, if any, during a particular season to maintain the level of consumption. This is a case of perfect consumption smoothing model.

In contrast, when $\beta_2 > 0$, we have a case of lack of consumption smoothing. Under this scenario, either of the following emerges. (i) $\beta_1 > \beta_2$. This means that seasonal income relative to total income exceeds consumption in a given season. That is, a greater fraction of seasonal crop income relative to total income is saved for managing consumption smoothing (Deaton 1997). (ii) $\beta_1 < \beta_2$. This indicates that households spend more than seasonal income relative to total income. This is possible for the following reasons: Households may draw income from non-crop or non-farm sources not included in total income or resort to distress sale of assets, or advance sale of labor and crop or family and intra-family transfers to augment income in a particular season to avoid starvation.

A major problem with the estimation of equation (3.1) is the joint distribution of income and consumption because of the presence of the errors (μ and η). There is substantial evidence for joint causation between income and consumption (Strauss 1986;

[19] It is assumed that the sample is uniformly distributed over the entire year, with enough observations from all seasons to carry out the analysis. For example, the distribution of 7,640 households sampled in 2005 HIES survey include 27% in season one, 22% households in season 2, 27% in season three, and 24% in season 4.

Strauss and Thomas 1995). More specifically, there are measurement errors in both income and consumption. For example, measurement errors in consumption are likely to be correlated with measurement errors in income, which would tend to induce an attenuation factor that biases coefficients towards zero (Deaton, 1997; Ravallion and Chaudhuri, 1997). In this case, even household panel does not help; we need to instrument income.

The instruments for income (*Y*) and its seasonal shares (*y*) can be the production constraints such as rainfall and a productive environment such as irrigation potential. The labor market clearing wages are also assumed to influence only income and not consumption directly. These variables are represented by the vector (*M*). Here we rely on the assumption of perfect substitutability model of income and consumption with an active labor market to justify the instrumental variable (IV) method (Singh, Squire, and Strauss, 1986).

In other words, the income equations can be written as:

$$\ln Y_{ijs} = \alpha^{Y}\tau_{s} + \gamma^{Y}X_{ij} + \delta^{Y}M_{ij} + \mu_{ij}^{Y} + \eta_{j}^{Y} + \varepsilon_{ijs}^{Y} \qquad (3.2)$$

$$y_{ijs} = \alpha^{y}\tau_{s} + \gamma^{y}X_{ij} + \delta^{y}M_{ij} + \mu_{ij}^{y} + \eta_{j}^{y} + \varepsilon_{ijs}^{y} \qquad (3.3)$$

A test of perfect consumption smoothing is carried out using the HIES of 2000 and 2005. The focus of analysis is to estimate a consumption model to demonstrate the extent of the net effect of income seasonality on consumption.[20]

Even with IV method based on cross-section data we will encounter another problem. That is, when we relate seasonal consumption to seasonality of income and non-income factors even after controlling for joint determination of income and consumption, we invariably introduce a common season effect such as seasonal shock that affects both

[20] Calculation of seasonal share of income from HIES data is done as follows. Household income was reported for the entire year and not by season in HIES. However, household's annual income from crop cultivation was disaggregated by season, because, barring few exceptions, crop type varies by season, and knowing the crops that a household cultivate we tracked its crop income down to a season. So, it's the share of seasonal crop income we used to proxy for income seasonality. This is a reasonable assumption, given that crop income fluctuation is the root cause of income seasonality in Bangladesh.

seasonal income and consumption. That is, it is possible that a common seasonal shock influences all households to behave in a certain manner, independent of household and village heterogeneity. For example, household consumption may be completely independent of seasonal variations in income and still co-vary with seasonal income, simply because of common season-specific shock.

Introducing seasonal dummies in the regression of (3.1) does not resolve this problem. Nor an introduction of a village fixed effects method can solve this either, as common seasonal effect affects all households equally in a village. This requires us to introduce a common seasonal model which requires seasonal panel data (i.e., repeated observations across seasons). Recall that cross-sectional data of 2000 and 2005 do not form panel either at the household or village level, but they provide a cross-section of households/villages interviewed across seasons over two years. In this case, one constructs a panel of seasons at the thana level if not at the village level with different households interviewed over two seasons. Thana is thus the lowest common sampling units that can help create the panel across seasons. The common seasonal effect at the thana level (μ_{sj}) is therefore an aggregate shock observed at the thana level that affects equally all households living in a particular thana. We propose, therefore, to use a thana level fixed effects method with panel seasonal data to control for the common seasonal shock.[21] In other words, let us rewrite the equation (3.1) as follows:

$$\ln C_{ijst} = \alpha\tau_{st} + \beta_1 \ln Y_{ijt} + \beta_2 y_{ijst} + \gamma X_{ijt} + \mu_{ij} + \mu_{sj} + \eta_j + \varepsilon_{ijst} \qquad (3.4)$$

where μ_{sj} is unobserved thana-level common seasonal shock, *j* stands for thana instead of village and *t* is year. Similarly, equations (3.2) and (3.3) will include a seasonal thana-specific

[21] The ideal panel could be at the household level, meaning the same households were interviewed in different seasons over two years.

common shock (μ_{sj}). In estimating (3.4) we apply a thana-level fixed-effects instrumental variable method (call it FE-IV) to eliminate bias due to unobserved thana-level common seasonal shock affecting the consumption and income variations, as well as controlling for the joint distribution of income and consumption due to time in-varying unobserved errors observed at the household and thana level .[22]

One potential problem of estimating equation (3.4) is bias due to attrition of some thanas from the thana level fixed-effects analysis. As indicated, the HIES data sets of 2000 and 2005 are not meant to be panel even at the thana level. Out of a total of 504 thanas in Bangladesh, there were 250 thanas included in the survey year of 2000 and 291 thanas in 2005. When we merge the data at the thana level over two years, we get a common set of 184 thanas to be included in the thana level panel.[23]

Thus, altogether 66 out of 250 thanas from 2000 survey were not available for panel analysis, implying an attrition rate of 26.4 percent. Attrition can bias estimates where it is nonrandom or selective. In that case, it may well ruin the advantages that seasonal panel data analysis is supposed to have and cross-sectional data may be a better choice. There is a large body of literature that demonstrates that even a high attrition rate is a non-issue as long as it is random (Alderman and others 2000; Fitzgerald, Gottschalk and Moffitt 1998; Thomas, Frankenberg and Smith 2001; Ziliak and Kniesner 1998). For example, Fitzgerald,

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[22] In practice, what we do is the following. First, we multiply thana dummy with seasonal dummy to create thana-season dummy. Since we have two seasons (monga and non-monga), the difference between these thana-season dummies cancels out season-specific unobserved effect within a thana (μ_{sj}). Since these thana-season dummies are also observed in two years, the difference between them in two years cancels out thana-specific fixed effect (η_j). Yet there is a possibility that household-level heterogeneity which cannot be cancelled out in this process may be included in thana-level heterogeneity, part of which can vary over time. Therefore, we use an IV method to take care of this time-varying heterogeneity. The IVs are the rainfall and other production constraints that affect only the household production and not the consumption directly. As before, we will include predicted total and seasonal income shares in estimating equation (3.4).

[23] Note that the reduced samples for the thana level panel data consists of 5,040 households with 25% in season 1, 23% in season two, 27% in season three, and 25% in season 4.

Gottschalk and Moffitt (1998) found from Michigan Panel Study of Income Dynamics (PSID) that households with lower earnings, lower educational levels and lower marriage propensities are more prone to attrition. Their dataset had a high 50 percent attrition rate, still they found that there is no relationship between attrition rate and magnitude of attrition bias and that even large attrition causes unbiased estimation if attrition is random.

One can formally test if attrition biases estimates, namely, if reduced sample size because of attrition matters in our estimation. The issue we would like to investigate is, what are the determinants of thana attrition and to what extent attrition biases the estimates? We carry out a formal test for attrition bias. We regress per capita consumption of 2000 on the exogenous X-variables (age, sex and education of household head, maximum education of household's adult males and females, and so on), attrition dummy (meaning 1 for those thanas which were absent in 2005 and 0 otherwise) and attrition dummy interacted with X-variables. Since our purpose is to determine whether coefficients of the explanatory variables differ for those thanas that were dropped from 2005, we will perform a joint significant test (F-test) of the attrition dummy and its interaction variables. A similar fit will be made for the HIES survey of 2005, where attrition dummy includes the thanas excluded in 2000 HIES survey.

4. Does income seasonality affect consumption?

This section discusses the results of the impact of income seasonality on consumption. Table 5 presents summary statistics of the outcome and explanatory variables. As Table 5 shows, most welfare indicators – both at household and village levels – improve from 2000 to 2005. For simplicity, the country is divided into two regions—greater Rangpur and the rest of the country. Although seasonal shares of crop income capture seasonality of agriculture, we also include a seasonal dummy (1 for lean season, and 0 otherwise) by assuming that there is a common non-crop seasonality that also matters for consumption variations across seasons.[24]

Table 6 presents the results with two-model specifications (one for total per capita consumption and the other for per capita food consumption). The results are reported with cross-sectional data for 2000 and 2005. First, we estimate the first stage of income equations of (3.2) and (3.3) (reported in appendix table A1) and use the predicted values in equation (3.1) to estimate the influence of predicted income and its seasonal crop shares on seasonal consumption per capita. We test the endogeneity of income and its seasonal share to justify the two-stage IV model.[25] The Hausman endogeneity test results (table 6) show that the two-stage technique is a valid strategy to estimate the consumption model.

Next, we consider the role of seasonal income shares in consumption, conditional on overall yearly income, for the cross-sectional estimates of 2000 and 2005. We do find that the coefficient of seasonal income shares is statistically significant and different from zero, at least in 2005. That is, our results reject the model of perfect consumption smoothing. In other words, seasonal crop income tracks seasonal consumption (both food and total consumption) significantly – a clear case of lack of consumption smoothing. Although per capita consumption is determined by overall income, it can also depend on its seasonal shares. For example, in 2005, a 10 percent increase in total income raises per capita food consumption by 2.1 percentage points while a similar percentage increase in seasonal crop income share raises food consumption by 17.0 percentage points. Note that this is

[24] This two-way classification of the country or the year is an attempt to highlight the differences between monga and non-monga periods or between Rangpur and the rest of the country. Note that Rangpur belongs to Rajshahi division, which is one of 6 divisions of Bangladesh. Similarly, there are 4 distinct seasons but we are collapsing 4 seasons into only 2 seasons.
[25] Appendix Table A shows complete first stage estimates of income equations.

independent of any other type of seasonality or imperfections (for instance, individual preferences or labor and product market imperfections) that may cause variations in consumption.

Can the finding of a lack of consumption smoothing be maintained with seasonal panel analysis where we control for bias due to common seasonal and aggregate income shock? Consider the seasonal panel data analysis of equation (3.4). As indicated, constructing thana level panel will invariably loses a few thanas as the HIES data collection over the survey periods of 2000 and 2005 is not meant to be even at the thana level. Therefore, a test of attrition bias for losing thanas in panel data analysis is done. The test results are shown in table 7. From the results we see that at 1 percent level, the null hypothesis of excluded thanas is the same as the included thanas cannot be rejected for both survey periods. Thus, we do not think attrition bias is an issue for the study and, therefore, we overlooked this issue in our estimation of thana-level panel data. In a panel household study, Ziliak and Kniesner (1998) reached the same conclusion, "…nonrandom attrition is of little concern …, because the effect of attrition is absorbed into the fixed-effects".

The FE-IV estimates of equation (3.4) are shown by the last two columns of table 6. The FE-IV estimates confirm that crop income seasonality still matters in consumption. For example, a 10 percent increase in seasonal crop income shares increases household's per capita total consumption by 16.6 percent and food consumption by 11.9 percent respectively. The results also confirm that households spend more than seasonal shares of total income to support consumption. This perhaps suggests that households either draw income from non-crop sources not included in seasonal income or resort to distress and advance sale of labor, crop, or assets or to inter-family transfers not reported in income data to smooth consumption.

Overall, the evidence suggests that changes in seasonal consumption track seasonal income, implying that households are unable to smooth consumption with crop income across seasons. This contradicts the null hypothesis of perfect consumption smoothing. The evidence is consistent with the findings from other countries as well (e.g., Kazianga and Udry 2006).[26] This finding supports that idiosyncratic shock matters in rural income and consumption.

Given that seasonal income matters, the next question is – does it matter more in Rangpur than in the rest of the country? Also when the common non-crop-income seasonality is measured by the monga dummy, does it matter in seasonal variations in consumption and does it matter more in Rangpur than in other regions? To address such issues, we modify equation (3.4) by adding 4 more variables: a seasonal dummy, a regional dummy (1 for greater Rangpur and 0 elsewhere), a seasonal share of income interacted with regional dummy, and the seasonal dummy interacted with the regional dummy. Note that the interaction term between seasonal and regional dummies represents an aggregate seasonal shock at the regional level as opposed to idiosyncratic shock as measured at household level by crop income shares.[27] In other words, we would like to test if idiosyncratic and aggregate consumption risks are greater in Rangpur than in other regions. We also introduce an interaction term of year and regional dummy to measure whether consumption growth differs by region. Table 6 also illustrates the results.[28]

[26] This finding contradicts the findings of Paxson (1993) for Thailand and those of Jacoby and Skoufias (1998) for India.

[27] See Jalan and Ravallion (1999). Alternatively, the aggregate shock could be measured by the village-level interaction terms with year or the average village consumption. This requires, however, household-level panel data, which we do not have.

[28] Besides the total and share of seasonal income, the interaction term between seasonal share and the Rangpur region is treated as endogenous in these estimations, which makes the observed t-statistics in the second stage biased. This bias has been corrected by bootstrapping the regressions.

As table 6 suggests, the impact of income seasonality (at least for food consumption) is more pronounced in Rangpur than in other regions. This is captured by the interaction term of seasonal income with the regional dummy. Thus, the impact of crop income seasonality in food consumption is 3 times higher in greater Rangpur than in the rest of Bangladesh. The finding suggests that idiosyncratic income risk is much more pronounced in Rangpur than in other regions.

The non-crop-income seasonality as captured by monga dummy influences both food and total consumption.[29] Thus, food consumption is lower during the *monga* (i.e., lean) than other periods. For example, a household's per capita food consumption decreased by 2.7 percentage points. Paradoxically, total consumption is at least 4 percent higher during the lean period than other periods. However, the negative food consumption effect of monga is much higher in greater Rangpur than in other regions. Therefore, households living in greater Rangpur suffer more from idiosyncratic and aggregate shocks. Seasonality of consumption is therefore more than income seasonality in greater Rangpur.

Surprisingly, this is despite the fact that the greater Rangpur region experiences a higher food consumption growth than other regions, as measured by the coefficient of the interaction term between year and regional dummy. Although consumption grew in all regions over the years, it grew at a higher rate in Rangpur than in other regions (at least for food consumption). But even if consumption grew at a higher rate, households still cannot cope with seasonality in income to smooth consumption in Rangpur as efficiently as in other areas of Bangladesh.

5. Does income seasonality affect poverty?

[29] The seasonal dummy may also capture the seasonal variation in non-crop income as the total includes yearly income received from all sources such as income from non-crop and non-agricultural sources.

With evidence of lack of consumption smoothing, we now ask: Does income seasonality affect all households equally, or does it vary depending on the level of poverty? Following Jalan and Ravallion (1999), a panel estimation regression (3.4) is run separately for poor and non-poor households.

Table 8 reports the results. Crop income seasonality affects everybody, although the magnitude seems to vary between poor and non-poor households. We test the coefficients of seasonality for equality between poor and non-poor households, and the chi-square test indicates that the coefficients vary significantly by all types of poverty status for per capita total consumption, and by food poverty only for food consumption. That is, income seasonality is much less pronounced for non-poor than poor households. In other words, consumption of non-poor households is much more insured against income shocks than that of poor households consistent with other studies (e.g., Jalan and Ravallion 1999).[30]

The above analysis, however, does not deal with the question of whether income seasonality affects poverty itself. If a lack of consumption smoothing is a major hurdle for many households, particularly among the poor, we expect that income seasonality would also affect the incidence of poverty. In fact, we have seen in section 2 that just like consumption poverty is sensitive to seasonality as well. To estimate the effect of seasonality on poverty, we follow two procedures: (i) We estimate the probability of a household's being in poverty against seasonal income a la equation (3.1) and (3.4); and (ii) we calculate the changes in poverty status based on the consumption estimates of equation (3.4) as reported in table 6.

Unlike consumption in equation (3.1), for example, the poverty is binary and hence, the equation is non-linear. However, for practical reasons, we used a FE-IV method to

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[30] Such a comparison is not truly meaningful, as consumption and poverty are jointly determined. Later we will treat seasonality in the context of poverty itself. Also note that as seasonality does not vary much by moderate poverty, we will focus on seasonality in the context of only food and extreme poverty.

estimate the linear probability of whether the household is poor in a given season.[31] Consider the following equation to estimate the poverty incidence.

$$\Pr(C_{ijst} < Z_t) = \alpha\tau_{st} + \beta_1 \ln Y_{ijt} + \beta_2 y_{ijst} + \gamma X_{ijt} + \mu_{ij} + \mu_{sj} + \eta_j + \varepsilon_{ijst} \qquad (5.1)$$

Here *Pr* measures the probability of consumption falling below the poverty threshold (*Z*). As before, we used a FE-IV method to estimate the linear probability model with predicted values of total income (*Y*) and seasonal income shares (*y*). The estimates of poverty effects of income seasonality following equation (5.1) are shown in Table 9.

Estimates suggest that total overall income is a major cause of both food and extreme poverty. According to FE-IV estimates, a 10 percent increase in total per capita income reduces food poverty by 1.9 percentage points and extreme poverty by 4.3 percentage points. Seasonal income shares affect poverty in a much more pronounced way. For example, a 10 percent increase in seasonal crop income shares can reduce food poverty by 9.2 percentage points and extreme poverty by as much as 13.2 percentage points. The substantive negative relationship between poverty and income seasonality indicates that seasonal income tracks seasonal poverty, making income seasonality a major cause of seasonal poverty.

Are these poverty estimates much different from those estimated using the second procedure? We follow the second procedure where we calculate the poverty effects using the consumption estimates of table 6. This essentially means we implement the following method:

$$\delta P / \delta y = (\delta P / \delta C)(\delta C / \delta y) \qquad (5.2),$$

[31] We use this linear two-stage fixed-effects method instead of the two-stage fixed-effects logit because FE-logit loses a lot of observation. Nonetheless, the linear probability estimates are asymptotically consistent.

where *P* indicates poverty measure. That is, given the consumption estimates of table 6, we calculate the likely consumption changes due to seasonality of income. Given the estimated consumption changes, we estimate how much poverty changes are likely due to changes in seasonal income shocks. The changes in poverty using this procedure are shown in table 10. The results clearly confirm that there is a negative impact of income seasonality on all measures of poverty, meaning seasonality in income affects poverty negatively. However, the calculated poverty effects of seasonality using the consumption estimates are lower than those obtained with a linear poverty model.[32] For example, a 10 percent increase in seasonal crop income can reduce food poverty by 9.2 percentage points as per the direct poverty estimates of Table 9 compared to only 1.8 percentage points as shown in Table 10. The magnitude varies considerably but the direction of change is the same.

The linear probability model of poverty shows the role of aggregate shock besides the role of idiosyncratic shock on poverty. It shows that seasonality in crop income is not a major factor causing poverty in Rangpur. This is demonstrated by the interaction terms of seasonal income shares and the region dummy.

But non-income seasonality plays an independent role in causing high incidences of food poverty. For example, food poverty is higher during the *monga* season by at least 3.4 percentage points. The interaction of the Rangpur region and the *monga* period is significantly negative for extreme poverty, suggesting that aggregate shock negatively affects extreme poverty more in Rangpur than other areas. Therefore, poverty is not so much due to idiosyncratic shock. Aggregate shock also matters a lot causing seasonal deprivation, remaining a major challenge in greater Rangpur for reducing seasonal hunger and chronic poverty.

[32] The difference could be attributed to the linearization of a non-linear model.

6. Policies to mitigate seasonality in income and poverty

What could be done to mitigate seasonal deprivation as persistent and widespread as in Rangpur? The basic hypothesis is that since seasonal poverty is caused by both idiosyncratic and aggregate shocks, which also affect chronic poverty (where chronic poverty in turn affects seasonal hunger and poverty), the mitigating policies must be broad-based as well as targeted. The broad-based policies could be, for example, infrastructural development programs that help promote overall income growth, and hence, income diversification. In contrast, targeted policies such as food for work (FFW) and vulnerable group feeding (FGF) could target the vulnerable households during the lean season.

In practice, as *monga* is determined by the interactions of income and non-income factors characterizing a rural economy, we must understand how certain regions such as greater Rangpur differs from other regions in terms of accessing public policies and programs. We already observed that households in non-Rangpur districts increasingly draw relatively more income from non-farm sources, including remittances, than farm sources than those living in Rangpur region. The non-Rangpur districts are also better endowed with resources that created improved access to formal credit, electricity, and a dynamic labor market.[33]

This raises a basic question of why policies differ by region. One may hypothesize that the underlying reasons for the differences in policy and program placement across regions are differential agroclimatic endowments and location factors characterizing a region. This is because these factors determine agricultural and other opportunities of a region,

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[33] A labor market is dynamic when real wage grows over time. This has actually happened in areas other than Rangpur parlty because of diffusion of modern farm technology and rural non-farm income expansion in conjunction with net out-migration.

thereby affecting both public and private investments (Binswanger, Khandker, and Rosenzweig 1993). In other words, agroclimatic endowments influencing returns to public and private investments must be poorer in greater Rangpur than other regions. This is why public investments in roads, markets, irrigation, and banks are lower in Rangpur and thus, affect adversely the incidence of seasonality in income, consumption, and poverty.

The question is -- how public policies and programs are to respond to the underlying factors causing the high incidence of seasonality in income and consumption, and hence, poverty. The paper's aim is to determine the mechanisms through which a range of infrastructure and credit policies have contributed to growth in total income and its seasonal shares, and also whether these policies have led to significant reduction of seasonal and chronic poverty.

This is equivalent to running a reduced-form equation where the consumption or poverty is expressed as a function of all price and non-price exogenous policy (e.g., public infrastructural and credit-related investments) variables (*M*) affecting both income and consumption, thereby poverty.[34] By substituting income equations (3.2) and (3.3) into consumption equation (3.4) and after suppressing seasonal effects, we get the following reduced-form consumption equation:

$$\ln C_{ijt} = \alpha \ \tau_t + \gamma X_{ijt} + \delta M_{jt} + \mu_{ij} + \eta_j + \varepsilon_{ijt} \qquad (6.1)$$

But public infrastructural and credit-related investments are not random; rather, these public investments are directly influenced by agroclimatic and other local area endowments, which also affect the agricultural and non-agricultural opportunities in a given thana or a village. Better-endowed thanas/villages might be likely targets in some instances (for example, public investments in roads may seek areas with better terrain and earnings

[34] Note that M consists of the rainfall, productive environmental factors and wages that were considered as instruments for the 1st stage regression of income equations presented in appendix table 1.

potential), whereas other investments such as safety net programs may target poorly endowed areas. Furthermore, local agroclimatic characteristics are also likely to be highly correlated with other potentially unobserved community features that could affect program placement, such as local political influence proxied by the distance of the village from a thana head quarter (Binswanger, Khandker, and Rosenzweig 1993).

Agroclimatic and location factors can be measured (φ_j) and unmeasured (ϖ_j). Given the rural context of the samples, (φ_j) can be characterized by soil quality, flood potential, temperature, sunshine, and related factors affecting the earnings opportunities of the locality.[35] Other village/thana locational variables, R_{it}, including variation in annual rainfall, can also affect village-level policy characteristics, M_{jt}. Along with a time-specific error term, ε_{jt}, this relationship can be specified additively as follows:

$$M_{jt} = \alpha_0 + \alpha_1\varphi_j + \alpha_2 R_{jt} + \varpi_j + \varepsilon_{jt} \qquad (6.2)$$

Household outcomes, C_{ijt}, according to equation (6.1), such as per capita expenditure are affected by these agroclimate endowments and resulting policies. Such interactions make it difficult to identify the precise role of infrastructure and other policy initiatives on income, expenditure, and poverty. Observed and unobserved village/thana endowments as well as income earning opportunities determine jointly both household and policy interventions, and hence, household level income and poverty. Unobserved heterogeneity at the thana/village level may therefore affect both the outcomes of interest and program placement.

As Binswanger, Khandker and Rosenzweig (1993) study shows, when both public policies and private investments are jointly determined by the same agroclimate and location

[35] Agroclimatic data were obtained from the Bangladesh Agricultural Research Council's website, http://www.barc.gov.bd/Data_Stat.htm .

factors, we need a panel data set to use a fixed-effects method to estimate the impacts of policies on private investments and outcomes of interest. In our case, we will use the thana level panel data to resolve the bias due to joint determination of program placement and outcomes of interest such as income and consumption.[36]

Regarding the specific question of how to treat program placement, one problem with estimating equation (6.2) is that the direct impact of the agroclimatic variables φ_j and ϖ_j cannot be determined. We could estimate these effects if the policy investments (*M*) were not a function of the unobserved agroclimatic variables, ϖ_j. This would be the case if the observed set of agroclimatic variables φ_j completely represented the set of local area endowments affecting placement of infrastructure and credit programs, and thus ϖ_j could be treated as random. In this case, a random-effects estimation of equation (6.2) is valid. We conduct Wu-Hausman test, specifying the unobserved effect as the vector of local agroclimatic characteristics, to see whether the fixed-effects or random-effects specification is appropriate.

<u>Effects of agroclimatic conditions on infrastructure, school, and credit interventions</u>

Following equation (6.2) described above, Table 11 presents the FE results for the effects of local agroclimatic conditions (interacted with year to obtain time-varying characteristics) on program placement. The Wu-Hausman tests indicate that the fixed-effects model is appropriate for explaining variation in these policies over time, and therefore only the fixed-effects estimates are reported. Table 11 shows that agroclimatic endowments explain as

[36] Even if some policy variables are measured at the village level, public investments are truly made at the thana level. Thus, if a particular thana receives funds for certain public investments, the village is likely to receive the same investment, and not the other way around. Hence, a thana-level fixed-effect is appropriate to measure the impacts of public policies.

much as 37 percent of variation in the growth of electrification, irrigation, microfinance institutions and other variables over the period. There are many potential ways to interpret the direction of the impacts of agroclimatic variation on these interventions.

As Table 11 shows, while electrification is inversely related to proximity to thana headquarter, substantial variation exists in the effects of local area endowments across policies. Flood potential has a detrimental effect on finance expansion over the period, for example, whereas school expansion has targeted areas with less flood potential. Medium-highland areas, however, have experienced higher rates of electrification but lower rates of expansion in school, agricultural banks, and Grameen Bank. Areas with excess rains attracted less electrification, Grameen Bank, and FFW programs, but more schools.

Effects of policies on per capita income and expenditure

Having established that agroclimate factors matter in policy and program placements, it is now important to estimate the effects of policies (*M*) net of the effects of agroclimate factors on seasonality income and poverty. The results of the consumption model of equation (6.1) with added agroclimate variables for per capita total and food expenditures are presented in Table 12.[37] Using these consumption estimates we calculate and present also the estimated effects of selected policies on three types of poverty—moderate, food, and extreme poverty. A Hausman test is done to test if the FE or Random effect is appropriate for the model; the chi-square statistic clearly shows that the FE model is more appropriate in estimating equation (6.1). A joint significance of all policy variables also show that these policies considered together is significant at 1 percent level.

[37] Even with this specification, it is possible that unobserved household level heterogeneity can influence the estimates. Hope the bias is reduced by controlling the role of agroclimate and rainfall variables observed at the community or thana level. The bias due to unobserved household heterogeneity could be best dealt if we had a household level panel data.

To combat poverty, the most effective means are human capital investments. The results of Table 12 show that lack of human and physical capital is a major source of both structural and seasonal poverty as well as lack of consumption smoothing. Thus, each additional year of education for the head of household increase total per capita expenditure by 2.4 percent and food consumption by 1.1 percent per year reducing both moderate (by 2.5 percentage points), food poverty (by 1 percentage point) and extreme poverty (by 3 percentage points). Consequently, public investments in secondary education infrastructure will help increase consumption as well as reduce poverty. Villages that have a secondary school, for example, are likely to have extreme poverty reduced by 4.3 percentage points, and moderate poverty by 3.7 percentage points. On the other hand, primary school presence helps reduce food poverty by 3.2 percentage points.

Both land and non-land assets have strong positive effects on consumption and negative effects on poverty with much stronger of the two being non-land assets. For example, a one percent increase in land asset holdings reduces extreme poverty by 3.2 percentage points, while a similar increase in non-land assets reduces extreme poverty by 12.8 percentage points. Therefore, a policy that stipulates asset transfers as a way to mitigate *monga* will have more beneficial effects focusing on transfer of non-land assets than land assets.

Electrification has expected substantial positive effects on consumption and, hence, negative effects on poverty and seasonal food deprivation. Households that have electricity are likely to have their per capita total consumption increased by 16.3 percent, and moderate poverty reduced by 14.6 percentage points, extreme poverty by 18.4 percentage points, and food poverty by 3.5 percentage points. Electricity connection provides opportunities for both farm and non-farm income expansion, which ultimately helps increase consumption and thus reduce poverty and seasonal food deprivation. On the other hand, irrigation helps enhance farm productivity and thus food consumption by 3.1 percents. This in turn reduces food poverty by 1.4 percentage points. Public investments on physical infrastructure such as rural electrification and irrigation have substantive payoffs in poverty reduction.[38]

The presence of agricultural banks does not seem to have any significant effect on consumption and poverty. But micro-credit programs, such as the Grameen Bank, help increase total consumption (by 4.4 percent) and hence, reduce both moderate poverty (by 4.5 percentage points) and extreme poverty (by 5.3 percentage points).[39] The Food for Work (FFW) program contributed substantially to overall per capita total consumption (by 6.9 percents) and food consumption (by 7.5 percents) with consequent reduction of moderate poverty (by 7.3 percentage points), food poverty (by 3.2 percentage points), and extreme poverty (by 8.1 percentage points). The FFW program is thus most appropriate for addressing seasonality both in income and consumption as well as containing seasonal and overall poverty. The Vulnerable Group Feeding (VGF) program also increases per capita total consumption and food consumption by 2.7 percents and 4.4 percents, respectively. This in turn reduces moderate poverty, food poverty and extreme poverty by 2.9, 2.0 and 3.4 percentage points respectively.

Do some of these programs have differential effect during the lean season on consumption and poverty? To demonstrate whether this is the case, the monga dummy is interacted with program variables such as Grameen Bank, FFW and VGF (results are not

[38] Rural road expansion is another public investment that may have beneficial effects on poverty. However, HIES data does not provide information on rural roads. But given that rural electrification or Grameen Bank expansion follows rural road expansion, the effects of electrification or Grameen Bank captures in part impact of roads.

[39] Given the estimated effect, this means 1.0 percent annual rate of extreme poverty reduction due to Grameen Bank with its village coverage as low as 23 percent in 2005. This finding is not different from the average estimated impact of micro-credit on village-level poverty using household-level panel analysis (see Khandker 2005).

shown here). The results support that Grameen Bank and FFW have substantial contribution to both food and total consumption per capita during the lean season, showing that these programs help smooth consumption.

In short, *monga* is caused substantially by seasonality of agriculture; yet policy interventions can be judiciously and selectively applied to reduce the intensity of both chronic and seasonal poverty by raising seasonal and overall income and productivity as well as food and non-food consumption.

7. Discussion

Monga is an acute form of seasonality in consumption and income that causes food deprivation. Households in an agrarian society face seasonality in income and consumption as part of the crop cycle in agriculture but they also learn how to manage seasonality through savings and other means. When *monga* or seasonal food deprivation occurs, this indicates a failure of the traditional means. Monga is also a failure of public policies created to provide safety nets to manage seasonality and, hence, *monga*.

Household data analysis of HIES 2000 and 2005 suggests that seasonality in consumption is acute in certain months of the year and that seasonal variations vary substantially by region. For example, overall consumption per capita is much lower and seasonal fluctuations in expenditures are much greater in Rangpur region than in other regions. The relative fluctuation in consumption is also larger for extreme than non-extreme poor and much more pronounced in greater Rangpur. Levels of consumption are, in general, lower overall in Bangladesh during *monga* period (September-November) than other seasons, but the shortfall is much more pronounced in Rangpur than in other regions.

Econometric analysis confirms that the perfect consumption smoothing model is rejected and that seasonal variations in income substantially track seasonal consumption and poverty. Lack of income smoothing is therefore a major factor causing seasonal food deprivation in Rangpur. Households likely resorted to traditional means (e.g., self-insurance, interfamily transfers, or borrowing from informal sources) to cope with extreme volatility or shortfalls in consumption. But these traditional methods are certainly inadequate; otherwise, the incidence of monga would not have occurred every other year, especially in Rangpur in such a scale.

Government institutions often employ short-term measures such as cash transfers, food-for-work, food coupons, and public works to mitigate *monga*. If variations in consumption were only transient in nature and are idiosyncratic across households, these interventions if properly targeted could have helped mitigate *monga*. However, *monga* has been a widespread phenomenon, which is caused by low income and low productivity – the sources of chronic or structural poverty. Interventions not geared toward enhancing income and productivity growth or programs not well targeted are not of much help in containing *monga*.

Group-based lending is an approach geared toward enhancing income and productivity for the poor but appears to have limited impact in mitigating *monga, especially in Rangpur,* for a number of reasons.[40] First, micro-credit has failed in general to reach hardcore or extreme poor who constitute the majority of *monga*-vulnerable households.

[40] Pitt and Khandker (2002) found that one of the reasons for micro-credit program participation was to facilitate consumption smoothing. Households who are unable to smooth consumption are more likely to participate in micro-credit programs. Micro-credit tends to encourage income earning activities that are less vulnerable to seasonality and thus helps borrowers to smooth consumption. This observation appears less valid regarding micro-credit operation in Rangpur; had micro-credit been more successful, Monga would not have been so pronounced in Rangpur. However, monga would have been affected by micro-credit but for poor agro climate, the presence and coverage of micro-credit including the Grameen Bank is low in Rangpur compared to the rest of the country.

Second, micro-credit programs have no provision for stand-alone consumption loans to help smooth consumption when self-insurance does not work. Third, the weekly repayment culture of micro-credit programs is at odds when pronounced seasonality limits the ability of micro-credit agencies to support new loans during *monga*. Finally, group-based lending works well when income variations are idiosyncratic so that group members may assist/insure other members during difficult times. But as seasonality is systemic during *monga*, affecting everyone within a group, the ability of mutual insurance is severely curtailed and the group as a whole has a greater incentive to collude on a strategy of default. Not surprisingly micro-credit programs such as the Grameen Bank have limited coverage in the greater Rangpur district characterized by high aggregate income risk.

Nonetheless, our results show that all the policies and programs discussed above have some favorable impacts on seasonal poverty. Micro-credit programs matter in reducing poverty; yet only 7 percent of rural households have access to the Grameen Bank in Rangpur compared to 23 percent in other regions. Access to micro-credit must be improved to mitigate poverty by targeting the hard-core poor not currently served with new products appropriate for them.

Our results also suggest that targeted programs such as VGF have a negative effect on poverty, and it is good that the coverage of the VGF in greater Rangpur is higher (85 percent) than in other regions (58 percent). While coverage of VGF is satisfactory in greater Rangpur, that of other programs (FFW for example) is very low (less than 30 percent). Yet we find that FFW has had some substantive impacts on poverty. For sustainable benefits, the coverage, as well as scope, of these programs may be enhanced and focused toward the most affected individuals or households.

On a similar positive role, we note that asset transfer programs such as the Char Livelihood Project (CLP) as introduced by GOB with help from DFID is likely to affect the extreme food consumption volatility in Rangpur. Yet the asset transfer program seems more effective for non-farm asset transfer than farm asset transfer.

Non-targeted programs such as public investments in electrification, irrigation, and schools are expected to promote income and productivity of rural people in both farm and non-farm production, and therefore can help mitigate seasonal poverty such as *monga*. Public investments in schooling, as well as irrigation, would attract further investments, which help promote income and consumption in general and reduce poverty of all forms in particular.

We conclude that if the policies were integrated and coordinated, the monga situation in Rangpur could have been much better like in other regions of Bangladesh. Program officials must be aware of the fact that *monga* is not only seasonal but also an outcome of high rates of extreme or hard-core poverty. Therefore, policy interventions must be both short- and long-term in nature. A judicious use of short-term interventions along with a long-term policy focusing on raising income and productivity would help diversify rural income and eradicate *monga* as well as structural poverty.

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Table 1: Poverty lines by region

Poverty line (Tk./month)	**Greater Rangpur**		**Rest of the country**		**Whole sample**	
	2000	**2005**	**2000**	**2005**	**2000**	**2005**
Total poverty line	582.0	605.9	654.9	653.0	648.3	648.6
Food poverty line	509.6	518.5	551.9	558.3	548.1	554.5
Observations	440	520	4,600	5,520	5,040	6,040

Sources: HIES surveys, 2002 and 2005.

Table 2: Distribution of food poverty (FP) and extreme poverty (EP) by season (%)

Period	**Greater Rangpur**		**Rest of the country**		**Whole country**	
	2000	**2005**	**2000**	**2005**	**2000**	**2005**
Monga season	FP=93.0 EP=66.0	FP=88.3 EP=48.3	FP=86.4 EP=43.9	FP=83.4 EP=31.6	FP=86.9 EP=45.6	FP=83.8 EP=33.0
Non-*monga* season	FP=79.5 EP=52.3	FP=76.8 EP=43.0	FP=79.6 EP=38.4	FP=76.3 EP=28.6	FP=79.6 EP=39.7	FP=76.4 EP=29.9
All seasons	FP=82.6 EP=55.5	FP=79.5 EP=44.2	FP=81.5 EP=39.9	FP=78.2 EP=29.4	FP=81.6 EP=41.8	FP=78.5 EP=31.1
Observations	440	520	4,600	5,520	5,040	6,040

Sources: HIES surveys, 2002 and 2005.

Table 3: District-level overall insecurity measures

Insecurity measures	**Greater Rangpur**		**Rest of the country**		**Whole sample**	
	2000	**2005**	**2000**	**2005**	**2000**	**2005**
Moderate poverty headcount (%)	70.9	61.0	54.8	43.5	56.3	45.1
Extreme poverty headcount (%)	60.9	47.9	39.9	29.4	41.8	31.1
Observations	440	520	4,600	5,520	5,040	6,040

Sources: HIES surveys, 2002 and 2005.

Table 4: Selected welfare indicators of rural households

Indicators	Greater Rangpur		Rest of the country		Whole sample	
	2000	2005	2000	2005	2000	2005
Household indicators						
Per capita farm income (A) (Tk./month)	269.9	318.3	288.2	256.3	286.5	262.2
Per capita non-farm income (B) (Tk./month)	216.1	258.0	378.2	376.5	363.4	365.2
Per capita non-earned income (C) (Tk./month)	130.3	72.0	235.8	294.5	226.2	273.4
Per capita total income (A+B+C) (Tk./month)	616.3	648.3	902.2	927.3	876.1	900.8
Share of seasonal crop income in total income	0.168	0.177	0.110	0.123	0.115	0.128
Per capita receipt from remittance (Tk./month)	17.9 (13.7)	17.1 (23.8)	106.7 (45.3)	132.6 (45.0)	98.6 (43.6)	121.7 (44.5)
Per capita receipt from safety net programs (Tk./month)	1.8 (1.4)	1.5 (2.1)	2.4 (1.0)	2.6 (0.8)	2.3 (1.0)	3.2 (1.2)
Per capita total expenditure (Tk./month)	541.6	630.4	740.5	875.7	722.4	890.2
Access to electricity (%)	6.6	17.9	19.9	31.2	18.7	30.0
Land asset (decimal)	82.0	123.7	84.3	152.6	84.1	149.9
Access to formal credit (%)	6.4	7.1	9.6	9.3	9.3	9.1
Community indicators						
Male wage (Tk./day)	44.0	46.3	65.4	64.7	63.5	62.9
Female wage (Tk./day)	31.0	37.0	48.2	43.1	46.6	42.5
Extent of land irrigation (%)	78.3	81.2	59.0	59.8	60.8	61.8
If community was affected by flood in last 5 years (%)	86.4	65.4	79.1	69.1	79.8	68.7
If community was affected by river erosion in last 5 years (%)	40.9	7.7	19.8	15.9	21.7	15.2
If community has Grameen Bank (%)	22.7	15.4	13.1	23.5	14.0	22.8
If community has agricultural bank (%)	22.7	11.5	12.5	15.0	13.5	14.7
If community has commercial bank (%)	27.3	19.2	17.5	19.5	18.4	19.5
If community has Food-for-work program (%)	50.0	26.9	53.4	27.8	53.1	27.7
If community has vulnerability group feeding program (%)	68.2	84.6	57.4	63.6	58.4	65.6
Observations	440	520	4,600	5,520	5,040	6,040

Note: Farm and non-farm income constitute household's earned income, as they are receipts from active employment. On the other hand, non-earned incomes are receipts from investments, assets, pensions, remittances, gifts/charities and safety net programs. Safety net programs are VGD, VGF, IFS, FFW (money), Test Relief, GR, Money for education, RMP, Old Age Pension, Freedom Fighters Pension, etc.

Figures in parentheses are share (%) of non-earned income. Monetary figures are CPI adjusted with base year 2000.

Sources: HIES surveys, 2002 and 2005.

Table 5: Summary statistics of outcome and selected explanatory variables

Variables	2000	2005	Panel
HH variables			
Per capita total consumption(Tk./month)	722.4 (462.7)	852.5 (781.7)	788.7 (648.5)
Per capita food consumption(Tk./month)	414.8 (200.5)	453.8 (225.6)	434.6 (214.6)
Per capita total income (Tk./month)	876.1 (2,053.7)	900.8 (1,090.9)	888.7 (1,635.5)
Seasonal crop income share in total income (%)	11.5 (29.0)	12.8 (32.2)	12.2 (30.7)
Region is greater Rangpur	0.09 (0.29)	0.09 (0.29)	0.09 (0.29)
Education of HH head (years)	2.65 (4.04)	2.86 (4.13)	2.76 (4.09)
Sex of HH Head (1=M, F=0)	0.91 (0.28)	0.89 (0.31)	0.90 (0.29)
Age of HH head (years)	44.6 (13.6)	46.0 (13.9)	45.3 (13.8)
HH land asset (decimals)	84.1 (252.7)	149.9 (316.1)	117.6 (288.6)
HH non-land asset (Tk.)	105,826.7 (229,549.8)	147,393.3 (101,911.0)	128,485.7 (179,223.8)
HH has electricity (1=Yes, 0=No)	0.19 (0.39)	0.30 (0.46)	0.24 (0.43)
Time-variant community variables			
Village distance to nearest thana (km)	10.8 (7.3)	12.7 (20.1)	11.7 (15.3)
Village distance to nearest district (km)	30.1 (17.9)	31.6 (29.9)	30.8 (24.8)
Proportion of village land irrigated	0.61 (0.29)	0.62 (0.32)	0.61 (0.31)
Village has any primary school (1=Yes, 0=No)	0.85 (0.36)	0.93 (0.26)	0.89 (0.32)
Village has any secondary school (1=Yes, 0=No)	0.52 (0.50)	0.93 (0.26)	0.73 (0.45)
Village has any agricultural bank (1=yes, 0=no)	0.13 (0.34)	0.15 (0.35)	0.14 (0.35)
Village has Grameen Bank (1=yes, 0=no)	0.14 (0.35)	0.23 (0.42)	0.18 (0.39)
Village has FFW program (1=yes, 0=no)	0.53 (0.50)	0.28 (0.45)	0.40 (0.49)
Village has VGF program (1=yes, 0=no)	0.58 (0.49)	0.66 (0.48)	0.62 (0.62)
Average monthly rainfall (mm)	189.27 (154.49)	212.62 (171.53)	202.00 (164.42)
Time-invariant community variables			
Number of sunny months per year	9.0 (1.2)	9.0 (1.2)	9.0 (1.2)
Proportion of high land	0.23 (0.17)	0.23 (0.17)	0.23 (0.17)

Proportion of medium high land	0.35 (0.17)	0.35 (0.17)	0.35 (0.17)
Proportion of flood-prone area	0.50 (0.25)	0.50 (0.25)	0.50 (0.25)
Excess rain per month (mm)	73.53 (54.14)	73.53 (54.14)	73.53 (54.14)
Observations	5,040	6,040	11,080

Note: Figures in parentheses are standard deviations.
Sources: HIES surveys, 2002 and 2005.

Table 6: IV Estimates of per capita consumption

Selected explanatory variables	**2000**		**2005**		**Thana-level Fixed Effect**	
	Total	**Food**	**Total**	**Food**	**Total**	**Food**
Per capita total income (Tk./month)	0.675 (16.73)	0.490 (13.44)	0.437 (10.14)	0.208 (5.27)	0.539 (20.31)	0.318 (13.47)
Seasonal crop income share	-0.533 (-1.32)	-0.395 (-1.19)	1.516 (3.44)	1.704 (4.15)	1.663 (6.99)	1.187 (5.60)
Seasonal crop income share* Greater Rangpur region	9.042 (2.59)	6.754 (2.34)	1.097 (0.39)	-0.734 (-0.28)	0.586 (0.38)	2.987 (2.20)
Monga period	-0.063 (-2.49)	-0.104 (-4.19)	-0.027 (-0.82)	-0.059 (-2.02)	0.042 (2.15)	-0.027 (-1.67)
Greater Rangpur region	-0.624 (-2.31)	-0.561 (-2.64)	-0.230 (-1.07)	-0.075 (-0.38)		
Monga period*Greater Rangpur region	0.511 (2.07)	0.385 (1.97)	0.187 (0.87)	0.081 (0.42)	0.082 (0.63)	0.297 (2.53)
Year (0=2000, 1=2005)					0.197 (6.61)	0.142 (5.36)
Year* Greater Rangpur region					-0.032 (-0.88)	0.127 (3.91)
R^2	0.196	0.202	0.327	0.204	0.403	0.203
Wu-Hausman F test for endogeneity	F(3,5015)= 142.078, p=0.000	F(3,5015)= 52.683, p=0.000	F(3,6015)= 79.890, p=0.000	F(3,6015)= 53.707, p=0.000	F(3,7431)= 147.827, p=0.000	F(3,7431)= 73.810, p=0.000
Observations	5,040	5,040	6,040	6,040	7,640	7,640

Note: Total income and consumption are expressed in log form. Income variables are treated endogenous and so instrumented. Instrumental variables are community infrastructure (distance to district and thana HQ, presence of schools, banks, NGOs and safety net programs) and agroclimate characteristics (rainfall, land elevation, average number of sunny months, share of flood-prone areas and excess rain amount per month). Figures in parentheses are t-statistics. Regressions include other household (head's sex, age, education, and land and non-land asset) and community variables (prices of consumer goods, daily wage, etc.). Sources: HIES surveys, 2002 and 2005.

Table 7: Test of bias due to exclusion of unmatched 2000 and 2005 thanas from panel analysis

Outcome variables	F (or χ^2)value	p>F (or p>χ^2)
Per capita total consumption from 2000 data	F(33,183)=1.25	0.182
Per capita food consumption from 2000 data	F(33,183)=1.03	0.429
Per capita total consumption from 2005 data	F(33,225)=0.79	0.787
Per capita food consumption from 2005 data	F(33,225)=0.77	0.807

Note: Null hypothesis is that excluded thanas are same as included thanas as far as outcome regressions are concerned.

Table 8: IV Estimates of per capita consumption for poor and non-poor households (FE-IV estimation with panel data: N=7,640)

Selected explanatory variables	Per capita total consumption					
	Moderate poor	Moderate non-poor	Food poor	Food non-poor	Extreme poor	Extreme non-poor
Per capita total income (Tk./month)	0.249 (8.38)	0.397 (11.41)	0.428 (14.70)	0.422 (8.76)	0.190 (5.40)	0.407 (13.61)
Seasonal crop income share	1.184 (5.12)	0.691 (2.74)	1.487 (6.03)	1.392 (3.98)	0.892 (4.13)	0.897 (4.16)
R^2	0.141	0.238	0.185	0.247	0.029	0.234
	χ^2 (1)=5.66, p>0.017		χ^2 (1)=6.95, p>0.008		χ^2 (1)=5.38, p>0.020	
	Per capita food consumption					
Per capita total income (Tk./month)	0.162 (5.03)	0.125 (3.56)	0.230 (9.67)	0.067 (1.79)	0.148 (3.46)	0.155 (5.78)
Seasonal share of crop income	0.926 (3.70)	0.168 (0.66)	1.176 (5.83)	0.495 (1.83)	0.694 (2.63)	0.486 (2.51)
R^2	0.091	0.023	0.102	0.008	0.030	0.029
	χ^2 (1)=1.37, p>0.242		χ^2 (1)=3.44, p>0.064		χ^2 (1)=0.22, p>0.638	

Note: Total income and consumption are expressed in log form. Income variables are treated endogenous and so instrumented. Instrumental variables are community infrastructure (distance to district and thana HQ, presence of schools, banks, NGOs and safety net programs) and agroclimate characteristics (rainfall, land elevation, average number of sunny months, share of flood-prone areas and excess rain amount per month). Figures in parentheses are t-statistics. Regressions include other household (head's sex, age, education, and land and non-land asset) and community variables (prices of consumer goods, daily wage, etc.). χ^2 test shows the equality of seasonal income between poor and non-poor households

Sources: HIES surveys, 2002 and 2005.

Table 9: IV Estimates of food and extreme poverty

Selected explanatory variables	2000		2005		FE-IV	
	Food poverty	Extreme poverty	Food poverty	Extreme poverty	Food poverty	Extreme poverty
Per capita total income (Tk./month)	-0.281 (-11.79)	-0.513 (-15.15)	-0.138 (-5.57)	-0.387 (-13.62)	-0.186 (-7.79)	-0.426 (-14.53)
Seasonal crop income share	0.282 (1.38)	-0.254 (-0.87)	-1.168 (-6.03)	-0.811 (-3.63)	-0.919 (-4.29)	-1.321 (-5.02)
Seasonal crop income share *Greater Rangpur region	-2.630 (-1.61)	-8.602 (-3.71)	-0.606 (-0.51)	0.879 (0.64)	-0.940 (-0.69)	-1.616 (-0.96)
Monga period	0.060 (4.12)	0.051 (2.50)	0.051 (3.53)	0.035 (2.11)	0.034 (1.91)	-0.014 (-0.66)
Greater Rangpur region	0.143 (1.22)	0.571 (3.41)	0.075 (0.84)	0.004 (0.04)		
Monga period* Greater Rangpur region	-0.195 (-1.76)	-0.544 (-3.46)	-0.129 (-1.38)	0.008 (0.08)	-0.085 (-0.71)	-0.263 (-1.80)
Year (0=2000, 1=2005)					-0.007 (-0.24)	-0.201 (-6.08)
*Year** Greater Rangpur region					0.027 (0.82)	0.027 (0.66)
R^2	0.193	0.012	0.122	0.090	0.152	0.208
Observations	5,040	5,040	6,040	6,040	7,640	7,640

Note: Total income and consumption are expressed in log form. Income variables are treated endogenous and so instrumented. Instrumental variables are community infrastructure (distance to district and thana HQ, presence of schools, banks, NGOs and safety net programs) and agroclimate characteristics (rainfall, land elevation, average number of sunny months, share of flood-prone areas and excess rain amount per month). Figures in parentheses are t-statistics. Regressions include other household (head's sex, age, education, and land and non-land asset) and community variables (prices of consumer goods, daily wage, etc.). χ^2 test shows the equality of seasonal income between poor and non-poor households

Sources: HIES surveys, 2002 and 2005.

Table 10: Calculated poverty estimates based on FE-IV estimates of per capita consumption reported in Table 6

Income variables	2000			2005			Panel		
	Moderate	Food	Extreme	Moderate	Food	Extreme	Moderate	Food	Extreme
Per capita total income Tk./month)	-0.327 (-16.73)	-0.123 (-13.44)	-0.436 (-16.73)	-0.209 (-10.14)	-0.088 (-5.27)	-0.422 (-10.14)	-0.268 (-20.31)	-0.108 (-13.47)	-0.437 (-20.31)
Seasonal crop income share	0.545 (1.32)	0.288 (1.19)	0.417 (1.32)	-0.319 (-3.44)	-0.203 (-4.15)	-0.643 (-3.44)	-0.368 (-6.99)	-0.180 (-5.60)	-0.601 (-6.99)

Note: Total income is expressed in log form.

Table 11: Impacts of agroclimate and distance variables on policy variables (thana level FE estimates, N=7.640)

	Household has electricity (1=yes, 0=no)	**Village has any primary school (1=yes, 0=no)**	**Village has any secondary school (1=yes, 0=no)**	**Village has any agricultural bank (1=yes, 0=no)**	**Village has any commercial bank (1=yes, 0=no)**	**Village has Grameen Bank (1=yes, 0=no)**	**Village has FFW program (1=yes, 0=no)**	**Village has VGF program (1=yes, 0=no)**
Year (0=2000, 1=2005)	0.240 (2.92)	-0.323 (-1.15)	0.423 (1.17)	0.459 (1.34)	0.358 (0.92)	1.301 (3.65)	0.446 (1.05)	0.050 (0.11)
Village distance to district HQ (km)	-0.003 (-5.51)	-0.001 (-0.58)	0.003 (1.06)	0.001 (0.21)	0.001 (0.30)	-0.001 (-0.40)	-0.001 (-0.20)	-0.005 (-1.57)
Average monthly rainfall during the season (mm)	-0.00002 (-0.39)	-0.0002 (-1.42)	-0.0001 (-0.38)	-0.00003 (-0.19)	0.00003 (0.19)	0.00002 (0.13)	0.0001 (0.48)	0.0002 (0.69)
Number of sunny months per year*year	-0.015 (-1.72)	0.096 (3.25)	-0.020 (-0.54)	0.019 (0.54)	0.008 (-0.20)	-0.056 (-1.49)	-0.045 (-1.00)	0.011 (0.23)
Proportion of high land*year	-0.169 (-2.30)	-0.693 (-2.77)	-0.027 (-0.08)	-0.356 (-1.17)	-0.056 (-0.16)	-0.543 (-1.71)	-0.652 (-1.73)	-0.390 (-0.96)
Proportion of medium high land*year	0.167 (2.05)	-0.493 (-1.78)	0.069 (0.19)	-0.953 (-2.82)	-0.194 (-0.51)	-0.896 (-2.55)	-0.502 (-1.20)	-0.216 (-0.48)
Proportion of flood-prone area *year	0.060 (1.25)	-0.469 (-2.87)	0.090 (0.43)	-0.417 (-2.09)	-0.288 (-1.28)	-0.435 (-2.10)	0.095 (0.38)	0.173 (0.66)
Excess rain per month (mm)*year	-0.00004 (-1.92)	0.002 (2.85)	0.001 (1.63)	0.0002 (0.23)	-0.001 (-0.69)	-0.002 (-1.94)	-0.002 (-1.62)	-0.001 (-0.96)
R^2	0.038	0.168	0.372	0.045	0.0149	0.079	0.261	0.031
Hausman test for suitability of FE vs. RE (χ^2 and $p>\chi^2$)	χ^2 (8)=30.75, $p>\chi^2$ =0.0002	χ^2 (8)=53.70, $p>\chi^2$ =0.000	χ^2 (8)=9.91, $p>\chi^2$ =0.271	χ^2 (8)=6.90, $p>\chi^2$ =0.440	χ^2 (8)=5.85, $p>\chi^2$ =0.664	χ^2 (8)=15.87, $p>\chi^2$ =0.044	χ^2 (8)=12.32, $p>\chi^2$ =0.090	χ^2 (8)=14.80, $p>\chi^2$ =0.063

Note: Figures in parentheses are t-statistics.

Table 12: Reduced-form FE estimates (thana level) of policy and program placements on consumption and poverty

Explanatory variables	Estimates of per capita expenditures		Poverty estimates based on consumption estimates		
	Total consumption	Food consumption	Moderate poverty	Food poverty	Extreme poverty
Head's education (years)	0.024 (19.51)	0.011 (10.49)	-0.025 (-19.51)	-0.006 (-10.49)	-0.030 (-19.51)
Log of land asset (decimal)	0.026 (9.16)	0.023 (9.38)	-0.026 (-9.16)	-0.012 (-9.38)	-0.032 (-9.16)
Log of non-land asset (Tk.)†	0.112 (19.51)	0.070 (17.45)	-0.108 (-19.51)	-0.030 (-17.45)	-0.128 (-19.51)
Household has electricity (1=yes, 0=no)	0.163 (13.02)	0.081 (7.26)	-0.146 (-13.02)	-0.035 (-7.26)	-0.184 (-13.02)
Proportion of irrigated land in village	-0.011 (-0.42)	0.031 (2.27)	0.013 (0.42)	-0.014 (-2.27)	0.016 (0.42)
Village has any primary school (1=yes, 0=no)	0.036 (1.32)	0.074 (3.10)	-0.036 (-1.32)	-0.032 (-3.10)	-0.043 (-1.32)
Village has any secondary school (1=yes, 0=no)	0.036 (1.72)	0.009 (0.47)	-0.037 (-1.72)	-0.005 (-0.47)	-0.043 (-1.72)
Village has any agricultural bank (1=yes, 0=no)	-0.014 (-0.64)	-0.002 (-0.08)	0.015 (0.64)	0.001 (0.08)	0.019 (0.64)
Village has Grameen Bank (1=yes, 0=no) †	0.044 (2.16)	-0.001 (-0.06)	-0.045 (-2.16)	0.001 (0.06)	-0.053 (-2.16)
Village has FFW program (1=yes, 0=no) †	0.069 (4.27)	0.075 (5.18)	-0.073 (-4.27)	-0.032 (-5.18)	-0.081 (-4.27)
Village has VGF program (1=yes, 0=no) †	0.027 (1.94)	0.044 (3.48)	-0.029 (-1.94)	-0.020 (-3.48)	-0.034 (-1.94)
R^2	0.371	0.249	-	-	-
Hausman test for suitability of FE vs. RE (χ^2 and $p>\chi^2$)	χ^2 (38)=88.77, $p>\chi^2$ =0.000	χ^2 (38)=138.69, $p>\chi^2$ =0.000	-	-	-
Joint significance of policy variables marked by †	χ^2 (4)=701.76, $p>\chi^2$=0.000	χ^2 (4)=387.99, $p>\chi^2$=0.000			
Observations	7,640	7,640	7,640	7,640	7,640

Note: Consumption variables are expressed in log form. Income variables are treated endogenous and so instrumented. Instrumental variables are community infrastructure (distance to district and thana HQ, presence of schools, banks, NGOs and safety net programs) and agroclimate characteristics (rainfall, land elevation, average number of sunny months, share of flood-prone areas and excess rain amount per month). Figures in parentheses are t-statistics. Regressions include other household (head's sex, age, education, and land and non-land asset) and community prices of consumer goods, daily wage, etc., community infrastructure (distance to district and thana HQ, presence of schools, banks, NGOs and safety net programs) and agroclimate characteristics (rainfall, land elevation, average number of sunny months, share of flood-prone areas and excess rain amount per month).

Sources: HIES surveys, 2002 and 2005.

Table A1: First stage regression outputs for IV estimates

Selected explanatory variables	2000		2005		Panel	
	Per capita total income (Tk./month)	**Seasonal crop income share**	**Per capita total income (Tk./month)**	**Seasonal crop income share**	**Per capita total income (Tk./month)**	**Seasonal crop income share**
Year (0=2000, 1=2005)	-	-	-	-	-0.801 (-4.19)	-0.008 (-0.28)
Monga period (1=Yes, 0=No)	-0.016 (-0.75)	-0.029 (-8.95)	0.040 (1.75)	-0.029 (-9.03)	0.045 (1.65)	-0.041 (-10.57)
Greater Rangpur region	-0.38 (-0.80)	0.004 (0.53)	-0.283 (-6.18)	0.017 (2.64)	-	-
Head's education (years)	0.019 (6.12)	-0.001 (-2.46)	0.028 (8.74)	-0.001 (-1.86)	0.025 (9.06)	-0.001 (-2.52)
Head's sex (1=M, 0=F)	-0.255 (-8.47)	0.009 (2.11)	-0.332 (-11.47)	0.014 (3.46)	-0.307 (-12.02)	0.014 (3.96)
Head's age (years)	-0.003 (-4.88)	-0.0003 (-3.10)	0.001 (2.18)	-0.0001 (-1.40)	-0.001 (-2.00)	-0.0001 (-1.17)
Log of land asset (decimal)	0.018 (3.92)	0.011 (16.23)	0.042 (6.56)	0.020 (22.25)	0.014 (2.95)	0.015 (22.68)
Log of non-land asset (Tk.)	0.244 (22.47)	0.008 (4.94)	0.105 (13.83)	0.002 (1.43)	0.155 (19.78)	0.003 (3.01)
Household has electricity (1=yes, 0=no)	0.168 (6.91)	-0.011 (-2.98)	0.233 (10.69)	-0.006 (-2.03)	0.228 (10.88)	-0.008 (-2.71)
Village distance to thana HQ (km)	-0.003 (-2.14)	0.0002 (1.01)	-0.002 (-2.66)	0.0001 (1.55)	-0.005 (-2.86)	0.0002 (0.95)
Village distance to district HQ (km)	0.0003 (0.67)	-0.0001 (-1.83)	-0.0002 (-0.54)	-0.0005 (-0.11)	0.002 (1.50)	0.00003 (0.21)
Proportion of village land irrigated	-0.056 (-1.71)	0.020 (4.16)	-0.036 (-1.08)	0.025 (5.34)	-0.035 (-0.76)	0.031 (4.68)
Village has any primary school (1=yes, 0=no)	-0.023 (-0.82)	0.011 (2.52)	-0.014 (-0.35)	-0.002 (-0.39)	0.009 (0.20)	-0.003 (-0.43)
Village has any secondary school (1=yes, 0=no)	0.063 (3.22)	-0.019 (-6.46)	0.027 (0.50)	0.038 (1.05)	0.110 (3.03)	-0.017 (-3.36)
Village has any agricultural bank (1=yes, 0=no)	-0.035 (-1.18)	-0.005 (-1.08)	-0.025 (-0.77)	-0.002 (-0.42)	-0.017 (-0.46)	-0.011 (-2.10)
Village has any commercial bank (1=yes, 0=no)	-0.059 (-2.30)	-0.002 (-0.42)	-0.035 (-1.18)	0.001 (0.22)	0.025 (0.79)	0.009 (1.91)
Village has Grameen Bank (1=yes, 0=no)	0.007 (0.27)	0.001 (0.13)	0.139 (4.76)	0.002 (0.56)	0.011 (0.31)	0.012 (2.39)
Village has FFW program (1=yes, 0=no)	0.005 (0.25)	-0.004 (-1.37)	-0.109 (-4.85)	-0.002 (-0.50)	-0.023 (-0.85)	-0.010 (-2.58)
Village has VGF program (1=yes, 0=no)	0.068 (3.51)	0.008 (2.73)	0.054 (2.54)	-0.010 (-3.25)	0.066 (2.76)	-0.001 (-0.37)

Table A1: First stage regression outputs for IV estimates (continued)

Selected explanatory variables	2000		2005		Panel	
	Per capita total income (Tk./month)	Seasonal crop income share	Per capita total income (Tk./month)	Seasonal crop income share	Per capita total income (Tk./month)	Seasonal crop income share
Village wage of males (Tk./day)	-0.0001 (-0.16)	-0.0002 (-0.19)	0.001 (0.96)	-0.0002 (-1.80)	-0.001 (-0.48)	0.0003 (1.83)
Village wage of females (Tk./day)	-0.001 (-158)	0.0002 (1.44)	0.002 (1.76)	-0.0001 (-1.06)	-0.003 (-2.44)	-0.0001 (-0.73)
Village wage of children (Tk./day)	0.003 (2.66)	-0.0003 (-0.22)	0.001 (0.71)	0.0003 (2.36)	0.0003 (0.20)	0.0002 (1.27)
Village price of rice (Tk./kg)	0.011 (2.61)	0.003 (4.57)	0.012 (2.23)	0.001 (1.58)	0.012 (2.16)	0.004 (4.90)
Village price of wheat (Tk./kg)	0.001 (0.24)	-0.003 (-3.39)	-0.002 (-0.48)	0.001 (1.37)	-0.009 (-1.42)	-0.001 (-0.69)
Village price of soybean oil (Tk./kg)	0.002 (1.19)	0.001 (3.63)	0.008 (1.90)	0.001 (1.70)	0.005 (1.48)	-0.001 (-1.73)
Village price of onion (Tk./kg)	0.002 (1.29)	-0.001 (-2.46)	-0.008 (-4.74)	-0.001 (-5.76)	0.002 (1.18)	-0.001 (-2.79)
Village price of beef (Tk./kg)	0.003 (2.98)	-0.0001 (-0.94)	0.004 (3.80)	-0.0003 (-1.83)	0.005 (3.41)	-0.001 (-2.58)
Village price of potato (Tk./kg)	0.005 (1.99)	-0.0002 (-0.53)	0.011 (1.64)	-0.003 (-3.55)	-0.003 (-0.74)	-0.001 (-1.47)
Village price of lentil (Tk./kg)	0.004 (2.61)	0.001 (3.54)	0.003 (1.55)	-0.0004 (-1.69)	0.007 (3.28)	0.0004 (1.28)
Village price of sugar (Tk./kg)	-0.0002 (-0.10)	-0.001 (-2.87)	0.009 (2.32)	0.001 (2.40)	0.001 (0.36)	-0.0003 (-0.51)
Village price of salt (Tk./kg)	0.009 (2.06)	-0.003 (-4.58)	0.004 (0.85)	-0.003 (-4.32)	0.007 (1.11)	-0.001 (-1.08)
Village price of milk (Tk./liter)	-0.001 (-0.64)	-0.001 (-3.85)	0.005 (1.48)	0.001 (1.91)	-0.006 (-3.05)	0.0001 (0.18)
Average monthly rainfall during the season (mm)	-0.00001 (-0.26)	-0.00004 (-4.56)	0.0001 (2.28)	-0.0001 (-7.81)	0.0001 (1.50)	-0.00005 (-4.46)
Number of sunny months per year	0.008 (0.67)	-0.001 (-0.74)	0.097 (8.75)	-0.003 (-1.77)	-	-
Proportion of high land	0.149 (1.79)	0.032 (2.60)	-0.438 (-5.37)	0.048 (4.16)	-	-
Proportion of medium high land	-0.341 (-3.58)	0.027 (1.93)	-0.517 (-5.39)	-0.012 (-0.85)	-	-
Proportion of flood-prone area	-0.055 (-1.04)	-0.003 (-0.36)	-0.161 (-2.93)	-0.014 (-1.77)	-	-
Excess rain per month (mm)	-0.0003 (-1.45)	-0.00003 (-.68)	-0.0001 (-0.52)	0.0001 (0.01)	-	-
Number of sunny months per year*year	-	-	-	-	0.101 (5.22)	-0.002 (-0.66)
Proportion of high land*year	-	-	-	-	-0.451 (-3.22)	0.033 (1.62)
Proportion of medium high land*year	-	-	-	-	-0.298 (-1.76)	0.023 (0.95)
Proportion of flood-prone area *year	-	-	-	-	-0.194 (-2.07)	0.015 (1.11)

Excess rain per month (mm)*year	-	-	-	-	0.001 (2.90)	-0.0001 (-1.43)
R^2	0.309	0.209	0.265	0.183	0.253	0.165
Observations	5,040	5,040	6,040	6,040	7,640	7,640

Note: Figures in parentheses below the coefficients are t-statistics.